European Journal of Operational Research 234 (2014) 119–126

Contents lists available at SciVerse ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Stochastics and Statistics

Updating a credit-scoring model based on new attributes without realization of actual data

Yong Han Ju, So Young Sohn *

Department of Information & Industrial Engineering, Yonsei University, 134 Shinchon-dong, Seoul 120-749, South Korea

ARTICLE INFO

Article history:
Available online 28 February 2013

Keywords:
Finance
Credit-scoring model
Exploratory factor analysis (EFA)
Logistic regression analysis
ANOVA
Small and medium enterprise

ABSTRACT

Funding small and medium-sized enterprises (SMEs) to support technological innovation is critical for national competitiveness. Technology credit scoring models are required for the selection of appropriate funding beneficiaries. Typically, a technology credit-scoring model consists of several attributes and new models must be derived every time these attributes are updated. However, it is not feasible to develop new models until sufficient historical evaluation data based on these new attributes will have accumulated. In order to resolve this limitation, we suggest the framework to update the technology credit scoring model. This framework consists of ways to construct new technology credit-scoring model by comparing alternative scenarios for various relationships between existing and new attributes based on explanatory factor analysis, analysis of variance, and logistic regression. Our approach can contribute to find the optimal scenario for updating a scoring model.

1. Introduction

Small and medium-sized enterprises (SMEs) occupy a large portion of all industries (Ebrahim et al., 2011). According to 2007 statistics reported by the Korean Federation of Small and Medium Business, SMEs account for 99.5% of the total enterprise, 76.9% of the total employment (Kim et al., 2011). There is a number of government policies intended to structurally and financially support these SMEs. One of these policies is a credit guarantee for SMEs that is awarded on the basis of technology. The credit guarantee policy provides financial support to SMEs suffering from insufficient investment from private financial institutions due to lack of collateral and has the goal of increasing SME's accessibility to private financing sources (Oh et al., 2009).

The government has encouraged the creation of new businesses and supported these SMEs via technology credit guarantee schemes to help accelerate economic growth and to decrease the unemployment rate, especially during the current economic downturn (Kang and Heshimati, 2008). However, this financial support must be selective to prevent wasteful expenditures. In order to select the promising SMEs, technology credit scoring model is used. Since the first attempt of development of technology credit scoring model by Sohn et al. (2005), many studies have been published, focusing on more accurate default prediction by adding behavioral characteristics or economic environment to update existing credit scoring models (Kočenda and Vojtek, 2009; Moon and Sohn, 2010; Paleologo et al., 2010). However, these studies have not addressed the issue of updating existing attributes in the credit scoring model. This is a very important issue, because technology credit-scoring models often need to be updated to reflect the changes due to mergers, separations, and deletions of existing attributes.

This paper proposes a method to update a credit-scoring model with new attributes. A new model can be fitted only after collecting data based on these new attributes. However, a new credit scoring is needed to select SMEs, even before new data are observed and utilized for a new credit model fitting. Upon unavailability of such data, we propose approaches to find a new technology credit scoring model based on potential relationships between new attributes and existing attributes. Several scenarios are formed to create new attributes from their potential relationship with existing attributes. Exploratory factor analysis (EFA) is used to reduce the multi-collinearity in new attributes. Using a logistic regression for loan default against resulting factors one can obtain a new credit scoring model. Analysis of Variance (ANOVA) is used to compare the performances of new credit scoring models created according to different scenarios regarding the relationship between existing and new attributes. As a result of ANOVA, we can find the optimal scenario in terms of prediction accuracy.

This paper is organized as follows: Section 2 explains the proposed methodology, and Section 3 applies the proposed approach to the evaluation of SMEs in Korea. Section 4 summarizes results of our study and suggests further areas of study.

2. Literature review

Credit guarantee scheme is an important part of enterprise financing, especially for small and medium-sized enterprises

* Corresponding author. Tel.: +82 2 2123 4014; fax: +82 2 364 7807.
E-mail address: sohns@yonsei.ac.kr (S.Y. Sohn).

0377-2217/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ejor.2013.02.030

which often are faced with difficulty in flow of private accounts. In order to support these SMEs, various credit guarantee schemes were actively used for corporate financing by Korea Credit Guarantee Funds (KCGFs), and Korea Technology Credit Guarantee Fund (KTCGF) in Korea (Shim, 2006), and credit guarantee amount keeps increasing over time (Moskovitch and Kim, 2008). Especially, KTCGF was established to help SMES get loan based on their technology. Therefore, evaluation of SMEs' technology is very important to reduce the risk involved in lending.

Currently, adverse selection and moral hazard problems are critical issues in lending for SMEs. Although the guarantee agencies sense the risk in terms of SME's default, they tend to give SMEs chances to innovate by allowing lending (Oh et al., 2009; Navajas, 2001; Lee et al., 2006; Stiglitz and Weiss, 1981). Moral hazard is high because borrowers are aware that guaranty fund will cover losses although borrowers become bankrupt (Oh et al., 2009). In order to reduce such risk, technology credit scoring model was introduced.

Since the first introduction of technology credit scoring model by Sohn et al. (2005), many related studies have been published (Sohn and Kim, 2007; Sohn et al., 2007, 2012; Kim and Sohn, 2007, 2010; Moon and Sohn, 2008a,b). These previous studies attempted to improve technology credit-scoring models within the context of existing evaluation attributes which can be matched with default/non-default of fund recipient SMEs.

However, previous investigators did not consider issues related to updating technology credit scoring model with new attributes which have not been applied for lending decision yet. Established credit-scoring models should be updated to reflect changes in attributes. Often, new attributes are modified forms of existing attributes. In updating process, we consider two different situations: (1) multiple existing attributes are merged into a new attribute and (2) existing attributes are redistributed to become part of several new attributes. In this paper, we suggest ways to deal with these two situations.

3. Proposed methodology

In order to support small and medium enterprises, technology credit guarantee fund has been established in Korea. This fund gives the credit warranty to SMEs which score highly in technology evaluation in terms of the 16 attributes. In Fig. 1, left side shows the 16 attributes used originally in the scorecard when deciding whether to guarantee applicant firms (Sohn et al., 2005). In this study, we consider several potential scenarios describing the relationships between existing and new attributes and identify an optimal scenario that assigns the most appropriate weights on the existing attributes for the new attributes.

Technology credit scorecard includes a total of 16 attributes (Fig. 1), which can be sorted into four categories: management, technology, marketability, and profitability. Management attributes describe CEO's ability in various areas, such as knowledge management, technology experience, management, funding supply, and human resources. These individual attributes are assigned a maximum of five points each. Technology attributes, which include superiority, technology commercialization, product competitiveness, and sales schedule, are assigned 10 points each. However, it is difficult to distinguish CEO's technology experience from knowledge management, while funding supply should be classified under profitability rather than management. Other possibly misclassified attributes are listed in the right-hand column of Fig. 1.

To update the credit-scoring model with new attributes, we considered two alternate cases of change. In the first case, multiple attributes are merged into a new attribute (e.g., P1&P2 (G1), P8&P9 (G7), and P4&P15 (G13)). In the second case, existing attribute is redistributed to become parts of several new attributes or a new attribute (e.g., P9 (G6, G7, G8)). When such changes are made by the first and second cases, scoring models may be updated by either approach (1) retaining the values of the original attributes for the first case scenario but identifying split ratios for the second case, or approach (2) identifying weights for existing attributes for

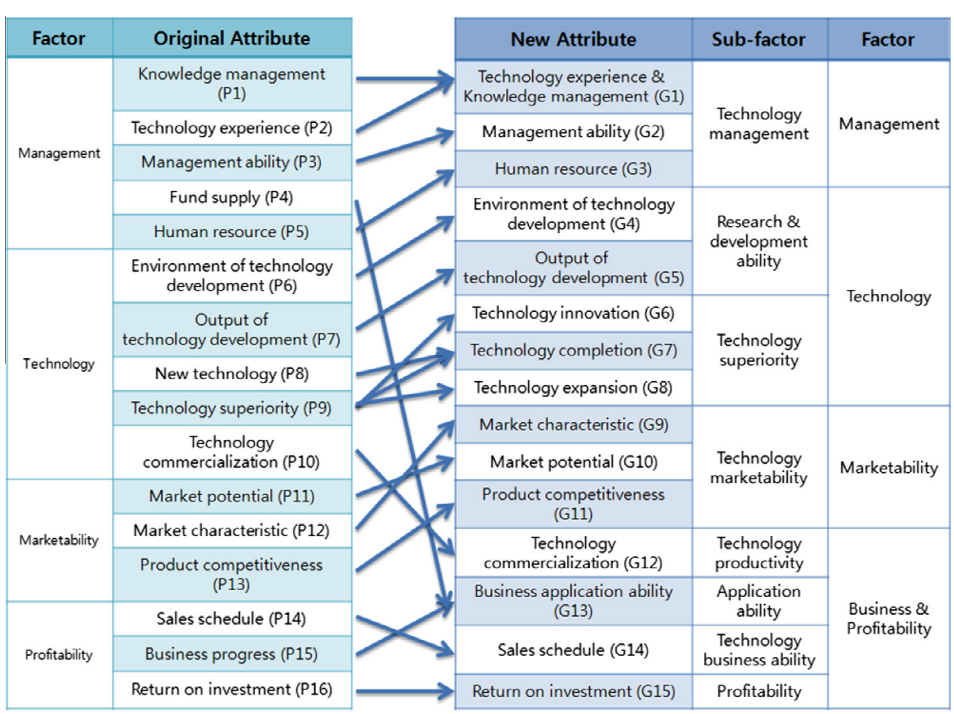

Fig. 1. Differences between existing and new scorecards.